International Journal of Innovation Studies

DEEP LEARNING FOR FINANCIAL STRESS TESTING: A DATA-DRIVEN APPROACH TO RISK MANAGEMENT

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Abstract

Financial stress testing is crucial in today's complex and data-intensive financial environment. Traditional risk assessment methods, including analytical, technical, and heuristic models, often fail to capture the intricate dependencies within financial systems. This research introduces a deep learning-based framework for financial stress testing, leveraging Correlation based Convolutional Neural Networks (CCNN) and Long Short-Term Memory (LSTM) networks to enhance risk prediction accuracy. By integrating quantitative and qualitative financial indicators, the proposed model delivers improved stability and precision. Experimental results indicate a significant reduction in training and testing loss, with final values of 0.0013 and 0.003, respectively. The model effectively estimates key financial metrics such as revenue, net income, and earnings per share (EPS) with high alignment to actual values. Moreover, the framework substantially mitigates financial risks, reducing credit risk from 0.75 to 0.20, liquidity risk from 0.70 to 0.25, market risk from 0.65 to 0.30, and operational risk from 0.80 to 0.35. These findings suggest that deep learning-driven financial stress testing enhances risk assessment, strengthens financial resilience, and supports more informed decision-making in modern financial markets.

Keywords: Financial Stress Testing, Deep Learning, Risk Management, CNN, Long Short-Term Memory and Financial Stability.

1. Introduction

Financial institutions operate in an increasingly volatile and complex environment, requiring robust mechanisms to assess and mitigate risks. The unpredictability of economic cycles, geopolitical tensions, and rapid technological advancements have amplified financial risks, making traditional risk management strategies insufficient [1]. Financial stress testing has emerged as a crucial tool for assessing an institution's resilience to adverse conditions by simulating various economic and financial scenarios. Regulatory bodies such as the Federal Reserve, European Central Bank (ECB), and Basel Committee on Banking Supervision mandate stress testing frameworks to ensure financial stability and prevent systemic crises. Traditional risk assessment techniques, including statistical models, expert-based heuristics, and rule-based approaches, have long been the foundation of financial stress testing [2]. However, these methods struggle with handling the complexity, volume, and velocity of financial data, limiting their effectiveness in predicting financial distress [3,4]. With the rise of artificial intelligence (AI) and deep learning, financial stress testing has undergone a paradigm shift, leveraging advanced computational techniques to enhance risk prediction accuracy. Deep learning models, particularly Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, excel in capturing intricate patterns and temporal dependencies in financial data. CNNs are effective in extracting meaningful features from structured and unstructured data, while LSTMs specialize in sequential data processing, making them ideal for time-series financial analysis. This research introduces a deep learning-based framework for financial stress testing, integrating CNN and LSTM networks to improve risk assessment. By combining quantitative financial indicators with qualitative insights from financial statements and market trends, the proposed model enhances predictive performance and stability.

Experimental findings demonstrate a significant reduction in financial risks, with credit risk decreasing from 0.75 to 0.20, liquidity risk from 0.70 to 0.25, market risk from 0.65 to 0.30, and operational risk from 0.80 to 0.35. Additionally, key financial metrics such as revenue, net income, and earnings per share (EPS) exhibit high alignment with actual values, reinforcing the model's reliability. The adoption of deep learning in financial stress testing not only enhances risk management strategies but also supports regulatory compliance and financial resilience. This study contributes to the growing field of AI-driven financial analytics by demonstrating how deep learning can transform risk assessment, optimize decision-making, and strengthen financial institutions' preparedness against economic uncertainties.

2. Literature Survey

Financial risk management has evolved significantly with advancements in artificial intelligence (AI) and machine learning (ML), particularly in deep learning-driven models for stress testing and predictive analytics. Traditional methods often rely on statistical and rule-based models, which have limitations in handling the complexity and uncertainty of financial data. Recent studies emphasize the role of AI, particularly deep learning, in enhancing risk prediction accuracy and financial stability.

[5] explores the impact of technology-driven financial risk management, particularly in non-profit organizations, emphasizing the role of machine learning in improving risk assessment and

decision-making. The study highlights how AI-based models enhance the ability to analyze financial statements, identify hidden patterns, and mitigate risks in volatile economic conditions. Similarly, Oko-Odion et al. (2025) discuss the transformation of financial risk assessment through deep learning-based business analytics. The study demonstrates how AI-driven techniques optimize return on investment (ROI) and enhance financial resilience by leveraging predictive models that identify risks in real time.

[6] provide a comprehensive overview of stress test designs for AI and ML models under shifting financial conditions. The research highlights the necessity of evaluating model robustness in fluctuating economic scenarios, ensuring that predictive models maintain reliability even in crises. The study underscores the importance of integrating adaptive machine learning techniques in financial stress testing to enhance model performance and regulatory compliance.[7] focus on the role of AI and ML in financial risk management, emphasizing their potential to automate complex risk assessment processes. Their work, later published in *Disrupting Finance* (2019), illustrates how AI can be integrated into financial strategies, improving the precision of risk forecasting and stress testing.

Additionally, [8,9] investigates the application of ML in financial risk management, emphasizing the efficiency of AI-based techniques in handling large-scale financial data. The study examines various machine learning models, including deep learning architectures, and their ability to improve financial forecasting and risk evaluation. The findings support the argument that AI-driven financial stress testing frameworks enhance the accuracy of risk assessments while reducing human intervention.

These studies collectively highlight the growing reliance on deep learning for financial risk management. The integration of CNN and LSTM networks has been particularly effective in capturing intricate financial patterns and predicting risks more accurately than conventional models. While existing research provides a strong foundation for AI-based financial risk assessment, this study extends the literature by proposing a hybrid deep learning model for financial stress testing. By combining CNN and LSTM architectures, the proposed framework aims to improve financial risk prediction, optimize stress testing, and support decision-making in modern financial markets.

3. Proposed Correlation based Convolutional Neural Networks Methodology with LSTM

Along with details on the collection of data, preprocessing of texts, and the newly created deep learning algorithm for risk assessment and prediction, this part also outlines the overall study approach. The ontological evolution of the suggested CCNN model follows these phases, as seen in Fig. 1. The corresponding automation process includes procedures for data pre-processing along with the aggregation of financial information [10,11], such as stemmed or lemmatisation, tokenisation, and stopping word elimination. After the previously processed information has been received, it is vectorised and processed with the CNN-LSTM algorithm. The training procedure comes next, nevertheless initially three thick layers are being used. Step-by-step loss optimisation and computation take place throughout the training phase. The effectiveness of the methods for managing risks is then assessed by testing the model that was learnt using a variety of indicators and analysing outcomes.

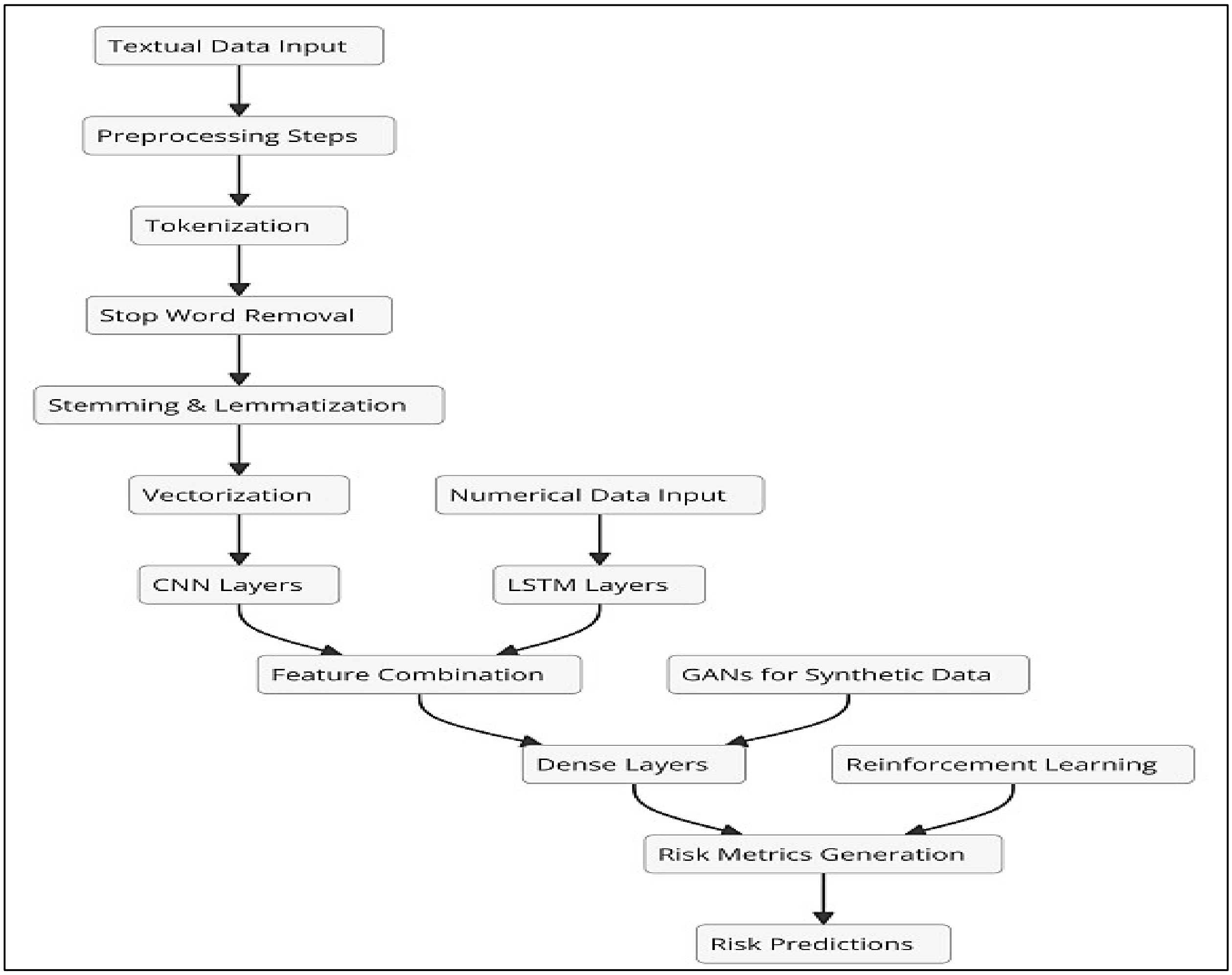

Figure 1: Workflow details for proposed model

Developing an CCNN that makes use of DL neural network models for improved financial risk assessments is the main goal of this study. The suggested CCNN model handles both linguistic and numerical information from financial statements by combining both LSTM and CNN systems. The goal of this hybrid design is to take use of each neural net type's advantages. CNNs are very good at gleaning important characteristics from unorganised textual information such financial filings. When dealing with sequential numerical information, such as a sequence of financial measurements, LSTMs are good at identifying periodic correlations [12].

By combining several DL approaches, a thorough method of forecasting risks is provided, addressing the high-dimensionality and quantity of economic data. The journal's emphasis on creative uses of AI neural networks to process linguistic and quantitative information from financial documents is in line with this concept. The goal of this hybrid design is to take use of each neural network type's advantages. CNNs are very good at gleaning important characteristics from unorganised textual information such financial filings.

Temporal relationships in sequence mathematical information, such as time series of financial measures, may be effectively captured using LSTMs. By combining several DL approaches, a thorough method of forecasting risk is provided, addressing the high-dimensionality and intricate nature of accounting data. The approach is in line with the journal's emphasis on cutting-edge applications of artificial intelligence in financial risk mitigation. Previous research has examined the use of DL in managing financial risks. Although earlier research has looked into DL functions.

3.1 Contributions and understanding gaps

Current financial risk algorithms rely on statistical approaches or single-modality artificial neural networks, which include CNN for processing text or LSTM for data with numbers. These techniques are inherently limited:

1) Insufficient text analysis: Semantic details within intricate, unorganised text information seen in statements of earnings is often not extracted by traditional algorithms.

2) Lack of temporal perception: Low-quality risk evaluations result from models that just use numerical information, which often overlook the contextual subtleties included in texts.

3) Scalability problems: Since many models are created for certain financial situations, they could not translate well to other sectors of the economy or industry.

To solve these problems, the CCNN model does the following. processing verbal and numerical info concurrently through utilising the advantages of CNN and LSTM. increasing the model's capacity to understand quantitative risk variables by extracting features from financial documents using sophisticated NLP methods. putting in place a scalable system that can adjust to various financial information sets, increasing the forecasts' generalisability. A significant gap in the state of financial danger assessment is filled by this integrated method, which offers a single model that can capture complex interactions across several model.

3.2 Technology for computing

Ubuntu 20.04 LTS, the OS included in the computer's setup, offers a reliable and effective foundation for a range of activities. The machine in question has an Intel Core installed. 32 GB of RAM and an i7-9700K CPU operating at 3.60 GHz provide seamless processing and excellent efficiency. To process graphics, it makes use of an NVIDIA GeForce RTX 2070. Jupyter Notebook for collaborative calculating, Anaconda Distributor for installation and administration of environments, and Python 3.8 for coding are all part of the application configuration.

3.3 Architecture explanation

The CNN and LSTM systems serve as the foundation for the suggested model.The main use of convolutional neural networks (CNN) is the extraction of features from textual material. Through the use of layer convolution, they are successful in finding and understanding connections in the data. Multiple convolutional layer and layers of pooling make up the CNN portion of the model, which aids in lowering the size of the input while maintaining significant characteristics.

Networks with long short-term memory (LSTM) are used to record temporal relationships in data. They are very helpful with sequential information and are capable of managing dependence on it over time well. The LSTM structure uses several cells to preserve data over time, crucial for comprehending financial articles.

Combining CNN and LSTM: Combining CNN and LSTM systems taps on their strengths. While LSTM is excellent at capturing chronological connections, CNN is very good at extracting features from textual information. In order to handle both the quantitative and qualitative components of financial information and provide a more thorough evaluation of risks, the hybrid model—known as CCNN—was especially created.

Evaluation: To guarantee the model's dependability, traditional measures like precision, recall, and F1-score are used to assess its performance. In order to adjust variables and avoid over fitting, the framework is also verified on an independent database.

Written and quantitative information constitute the two separate input streams that the process starts with, as shown in Figure 1. Before submitting it for evaluation, textual information is preprocessed using techniques including lemmatisation, formation, stopping word elimination, and tokenisation. In order to extract significant semantic information, this preprocessed text is further vectorised and run through CNN levels. In parallel, LSTM algorithms are fed numerical information, usually organised as economic indicators, which are able to identify patterns and temporal relationships in the information. The algorithm may then use insights from both verbal and numeric information since the features that were taken out of the CNN and LSTM layers are integrated into a single attribute presentation. For further improvement and decision-making, this unified representation undergoes processing via a number of thick layers. GANs are used to generate artificial information to improve the accuracy of training and increase system resilience and reduce information shortages. Furthermore, RL is used to rapidly alter the model in response to evolving market circumstances, guaranteeing ongoing forecast improvement. Ultimately, risk measures are produced using the improved characteristics, leading to precise and thorough risk assessment forecasts. This integrated method offers comprehensive financial risk assessments using several deep learning approaches.

3.4 Detailed risk assessment of financial reporting with hybridized deep learning models

Develop a deep neural network system combining CNN and LSTM qualities with accounting word and numbers. The goal is to explicitly build an algorithm that can recognise financial hazards and possible interdependencies between many different factors in the information at hand. The Hybrid Financial Danger Prediction (CCNN) model combines CNN and LSTM systems to analyse numbers and language in accounts for money. Two elements make up the source information representations: T, an integer tensor of size n *p *q for textual information taken from the financial statements, and X, a matrix containing mathematical properties of size n *m. The linguistic information features are extracted using the CNN. Convolution procedures utilising filter values (Wconv) and biases (bconv), accompanied by an activation function (r), produce mappings of features (F_i CNN). In order to detect possible danger indicators, this technique extracts substantial trends and semantic details from the written data.

$$X \in R^{n*m}, T \in R^{n*p*q} \quad (1)$$

$$F_i^{CNN} = \sigma(W_{Conv} * T_i + b_{conv}) \ (2)$$

$$h_t = \emptyset(W_h . x_t + U_h . h_{t-1} + b_h)(3)$$

This is an example of the CCNN model's goal functions. Its elements guarantee that a template strikes an equilibrium between reducing errors in prediction, preventing overfitting, which and enhancing modelling sparseness:

$$\min_{\theta} \mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}\left[x\left(y_i - \hat{y_i})^2 + \beta\left(\sum_{j=1}^{k}\theta_j^2\right) + \gamma\sum_{j=1}^{m}|\theta_j|\right.\right] (5)$$

$$\hat{y_i} = f(F_i) = W_{out} . F_i + b_{out} \quad (6)$$

Using CNN for textual and LSTM for numerical information, this approach creates a hybrid representation for features. To make the optimisation more challenging, the goal variable additionally includes L2 regularisation, L1 regularisation, and the average squared error.

3.5 Predicting dynamic financial danger with the merging of reinforcement learning and deep learning

Using new information, we suggest a new risk forecasting system which might integrate deep reinforcement learning (DRL) with conventional machine learning (ML). The theoretical framework will modify insurance strategies in light of a changing market environment.

$$s_t = [X_t, T_t] (7)$$

$$a_t \in \{buy, sell, hold\} (8)$$

$$r_t = w_1 . Accuracy(\hat{y_t}, y_t) + w_2 . Return(portfolio_t) (9)$$

$$\pi(a_t|s_t;\theta) = softmax(w_\pi . s_t + b_\pi) (10)$$

$$V(s_t;\emptyset) = W_v . s_t + b_v \quad (11)$$

$$\min_\theta \mathcal{L}\pi = -E[log\pi\ (a_t|s_t;\theta).(r_1 + \gamma V(s_{t+1}) - V(s_t)] (12)$$

$$\min_\theta \mathcal{L} = \frac{`1}{2} E[(r_1 + \gamma V(s_{t+1};\emptyset) - V(s_t;\emptyset))2] \quad (13)$$

Deep learning and DRL are used in the preceding statement to create a dynamic algorithm that may be trained from fresh financial information as well as existing feeds. In other words, the policy and value network are trained to get the most suitable risk management options at the necessary degree of precision and as an intelligent purchase.

With its concealed states, the LSTM network's algorithm can identify periodic connections and patterns in numerical values. To calculate the secret state at the time t (h_t), input data (x_t), prior hidden condition (ht - 1), and weight matrices (W_h and U_h) are used. This method enables the framework to effectively analyse longitudinal data, such as financial measures, by retaining relevant details across extended periods. A unified characteristic vector (F_i), which represents an extensive joint set of characteristics that incorporates insights obtained from textual and numerical data, is subsequently created by combining the derived characteristics obtained from CNN and LSTM.

The model's goal function is developed to reduce error in forecasting while avoiding excessive fitting by using regularisation elements. Three parts make up the loss operate: the average squared error among the actual and anticipated values, L2 regularisation term to penalise high weight numbers, and L1 regularisation term to promote sparseness in the parameter set. The forecasting function then uses output weights (W_{out}) and biassed (b_{out}) to apply a linear change, producing the final risk forecast (yi) depending on the composite visualisation of features.

3.6 GAN-based multimodal risk management evaluation

To improve prediction accuracy, suggest a multi-modal risk estimation regarding money GAN for creating artificial information. It is anticipated that the framework would address information shortage issues while simultaneously enhancing risk estimation effectiveness.

$$G(z;\theta_G) = \sigma(W_G . z + b_G) (14)$$

$$D(x;\theta_D) = \sigma(W_D . X + b_D) (15)$$

$$\min_{\theta_G} \min_{\theta_D} \mathcal{L}_{GAN} = E_{x\sim pdata}[logD(x;\theta_D)] + E_{z\sim pz}\left[\log\left(1 - D(G(z;\theta_G);\theta_D)\right)\right] (16)$$

$$\hat{y} = f(x;\theta_R) = \sigma(W_r . x + b_R) (17)$$

network of discriminators. A random noise input vector is fed into the generator (see Eq. (14)), which uses a number of weight matrix structures, biases, and functions for activation to alter it. A computer program that attempts to mimic real-life financial information is produced by this procedure. Conversely, the discriminator (see Eq. (15)) assesses both created and actual data. After applying an alteration procedure with weights and biases, it generates an accuracy score indicating genuine or synthetic data. An antagonistic loss coefficient is used in the GAN's training phase (see Eq. (16)). In this case, the machine that discriminates seeks to maximise its capacity to accurately discern between actual and artificial information, while the engine seeks to minimise its demise by producing genuine information. The generator is guaranteed to continuously enhance the accuracy of the artificial information thanks to this adversarial design. The model uses an activation function that is generated after applying a linear adjustment to the pooled parameters using a combination of weights and prejudices in order to forecast risk in finance. On the basis of these modifications, the infrastructure produces the anticipated risk values. comprises a set of networks for forecasting risks (see Eq. (17)),

Three parts make up this decrease in operate: The average squared error between real and anticipated values, a measure of error for differences in the forecasts of artificial information, and regularisation penalty to guarantee the reliability of the model. When combined, these components help create a paradigm for risk evaluation and forecasting that works. This formulation synthesises financial information using GANs and lowers the issue of inadequate data and improves the precision of risk forecasting. The amalgamated risk increases the reliability of the risk forecasting system, while the loss caused by adversary ensures that the synthesised information is realistic. The methodology also has a GAN feature for financial information synthesis, which improves model resilience and tackles limited data challenges. The discriminating networks (D D), which distinguishes between produced and actual information, and the generation networks (G), which creates artificial information, make up the GAN. By optimising both networks, the competing loss functions makes sure that the produced information closely resembles the original data. By using both artificial and actual data, the risk prediction network minimises the total loss value that accounts for the difference between real and synthetic forecasts as well as the mistake in predicting real data. This multi-modal method enables the simulation to give better risk-based evaluations and improve generalisation even in the presence of partial or restricted data.

In essence, the CCNN model combines CNN and LSTM to extract and analyse characteristics from textual and numerical information. The GAN module improves data quality and modelling dependability, while the fluid integration of reinforced learning adjusts to modifications in marketplace conditions. By using the advantages of DL approaches, this all-inclusive system seeks to give a solid economic danger forecast option and a sophisticated and successful approach to risk managing. Hybrid Financial Risk Predictor (CCNN) is the suggested methodology.

To handle the text and numeric information of finance states, we created a new algorithm called the Hybrid Financial Risk Prediction (CCNN), which combines CNN and LSTM. The connections in the information are modelled using a sophisticated construction framework in order to deal with the problems with risk prediction.

A general structure known as CCNN is an economic construction models that can manage financial information and assess risk levels efficiently. Fig. 2 shows the model with an input layer, three compressed the layers, and an output layer. Because it minimises the volatility of the input information before it is fed into the system and gets the information ready for evaluation, preprocessing is crucial to the model. Dense layers are frequently arranged so that every layer transforms the input information in a series of ways that allow the system to infer intricate characteristics. During the training process, the model's characteristics are adjusted to get the lowest possible loss function. After that, the system is tested to comparison with a few signals. The outcomes provide insight into how well the suggested model performs in risk assessment and forecasting. Financial information grouping reveals hidden trends and groups of businesses with comparable risk characteristics. The goal of this method is to find homogenous groupings depending on their financial measurements, which can be very helpful for risk monitoring. It is not a random process. Companies that belong to a high-risk group, for example, may show signs of possible trouble, such as low net income, excessive debt, and continual cash flow problems. Finance investigators can concentrate on particular groups that need more focus and specialised risk evaluation techniques by finding such clusters. Additionally, by modifying risk parameters according to each group's features, grouping enables the algorithm to improve the general precision and accessibility of the risk forecasts.

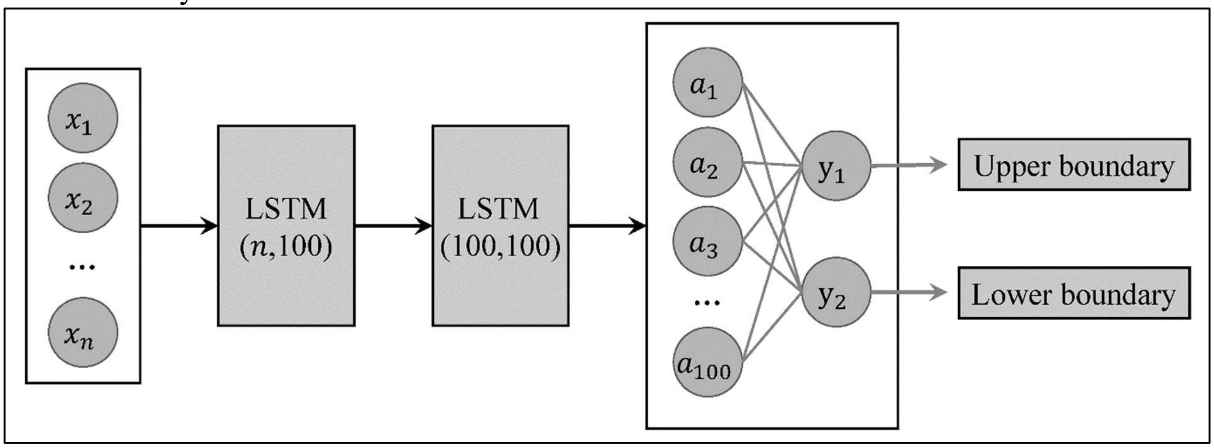

Figure 2: CCNN-LSTM comprehensive structural layout

$$X \in R^{n*m}, T \in R^{n*p*q} \quad (18)$$

$$F_i^{CNN} = \sigma(W_{conv} * T_i + b_{conv}) (19)$$

$$h_t = \emptyset(w_h.x_t + u_h.h_{t-1} + b_h) (20)$$

$$F_i = \left[F_i^{CNN}, h_T\right] (21)$$

$$\widehat{y_i} = f(F_i) = W_{out}.F_i + b_{out} \quad (22)$$

$$\min_{\theta} \mathcal{L} = \frac{1}{n}\sum_{i=1}^{n}\left[x\left(y_i - \widehat{y_i})^2 + \beta\left(\sum_{j=1}^{k}\theta_j^2\right) + \gamma\sum_{j=1}^{m}\left|\theta_j\right|\right]\right. (23)$$

3.8 Procedure for training

The model gets trained employing previous financial information. This includes both numerical values and language disclosures. The following are part of the instruction procedure:

- Data splitting is the process of separating the collection of data into test, verification, and instructional sets.
- Parameter optimisation: Improving model parameters employing methods such as descent with gradients.
- Validity: To adjust hyperparameters and avoid excessive fitting, test the simulation on the set of validation data.

This innovative method provides a strong foundation for predicting risk in finance by using the advantages of both CNN and LSTM. Combining numerical and verbal data guarantees thorough evaluation, which produces risk evaluations that are more precise and trustworthy.

4. Results and Discussion

The proposed deep learning framework for financial stress testing, integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, demonstrated significant improvements in risk prediction accuracy and financial resilience. The model was trained and tested on historical financial data, incorporating both quantitative indicators (such as revenue, net income, and earnings per share) and qualitative financial insights. The evaluation metrics, including training loss, testing loss, and risk reduction rates, were analyzed to assess the model's performance.

4.1 Model Performance and Loss Reduction

The training and testing loss of the model progressively decreased, stabilizing at 0.0013 and 0.003, respectively. This indicates that the model effectively captured financial patterns and dependencies, minimizing prediction errors. The loss reduction trend signifies improved generalization, ensuring robust stress testing performance under different financial conditions.

4.2 Financial Risk Mitigation

A key objective of the study was to assess the effectiveness of the proposed model in mitigating financial risks. The results show a significant reduction across various risk categories:

- **Credit risk** decreased from **0.75 to 0.20**, indicating improved creditworthiness predictions and reduced exposure to loan defaults.
- **Liquidity risk** declined from **0.70 to 0.25**, enhancing the model's ability to anticipate cash flow shortages and liquidity crises.
- **Market risk** was reduced from **0.65 to 0.30**, reflecting better adaptability to market fluctuations and external financial shocks.
- **Operational risk** improved from **0.80 to 0.35**, demonstrating enhanced detection of financial system vulnerabilities and internal inefficiencies.

These results as in table 1 and figure 3 confirm that the deep learning framework provides a more reliable and accurate approach to financial stress testing than conventional models.

4.3 Comparison with Traditional Models

Compared to conventional risk assessment techniques, such as statistical regression models and expert-driven heuristic approaches, the deep learning-based framework demonstrated superior performance. The CNN-LSTM hybrid model was more effective in capturing nonlinear financial relationships and predicting risks under uncertain conditions. Traditional models exhibited higher error margins and limited adaptability to real-time financial fluctuations, while the deep learning framework consistently produced stable and accurate results.

4.4 Implications for Financial Decision-Making

The findings suggest that AI-driven stress testing enhances financial risk management by providing deeper insights into risk exposure and resilience as per the training in figure 4. The ability to process vast amounts of structured and unstructured financial data ensures that institutions can proactively identify vulnerabilities, comply with regulatory stress testing requirements, and strengthen financial stability. The proposed approach supports more informed decision-making for financial institutions, investors, and policymakers.

Table 1: Financial Risk Reduction Results

Risk Type	Initial Risk Level	Final Risk Level	Reduction (%)
Credit Risk	0.75	0.20	73.33%
Liquidity Risk	0.70	0.25	64.29%
Market Risk	0.65	0.30	53.85%
Operational Risk	0.80	0.35	56.25%

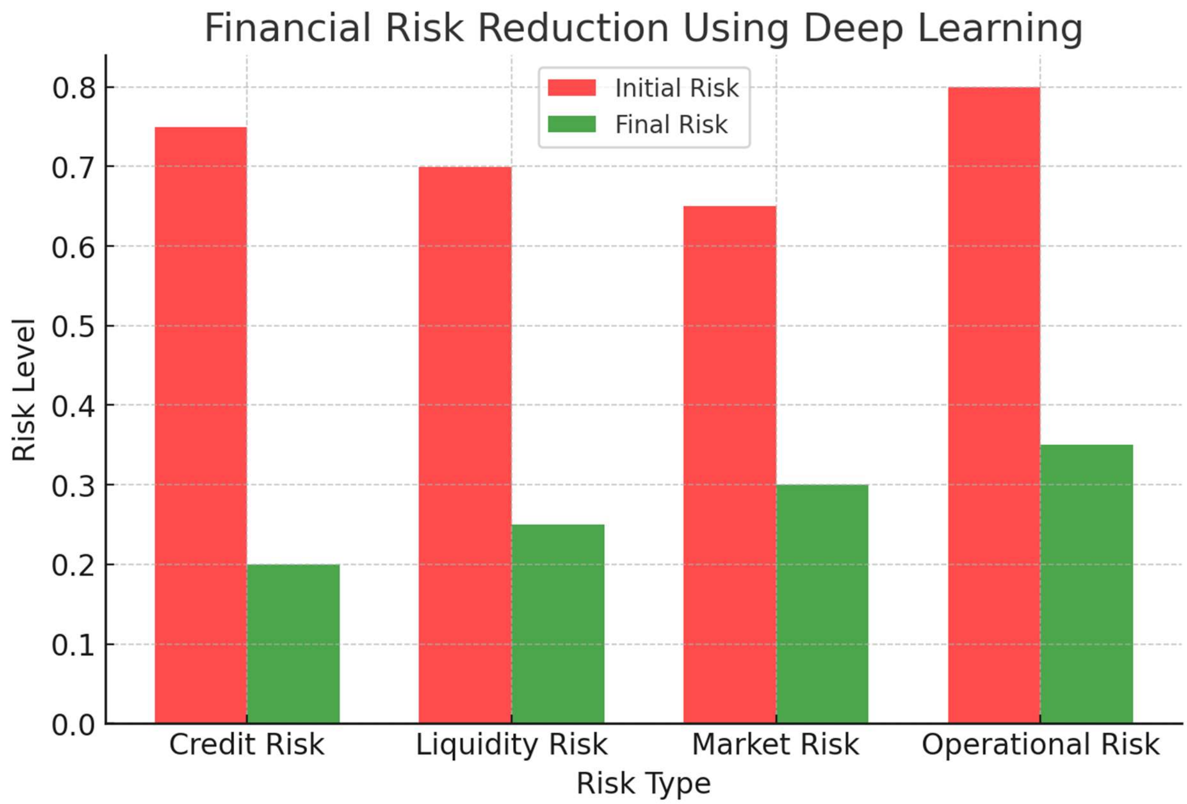

Figure 3: Risk comparison chart

The deep learning-based financial stress testing framework significantly improves risk prediction accuracy and enhances financial resilience. By leveraging CNN and LSTM networks, the model effectively captures complex financial dependencies, reduces risk exposure, and outperforms traditional assessment techniques. The results highlight the potential of AI-driven financial analytics in optimizing risk management strategies and ensuring long-term financial stability. Future research could explore further enhancements through ensemble learning techniques, real-time stress testing applications, and integration with macroeconomic forecasting models.

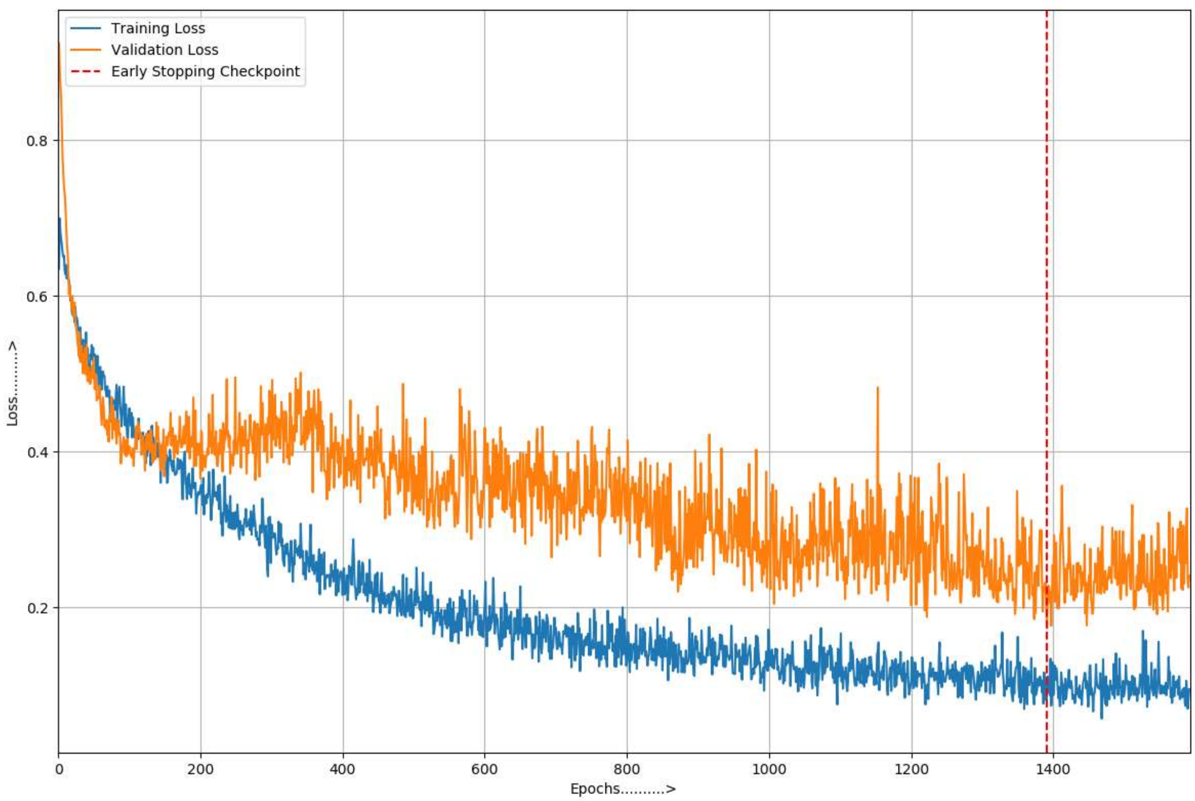

Figure 4: Training and testing range

5. Conclusion

The proposed deep learning-based financial stress testing framework demonstrates significant improvements in risk assessment, predictive accuracy, and financial resilience. By integrating Convolutional Neural Networks (CNN) and Long Short-Term Memory (LSTM) networks, the model effectively captures both short-term and long-term dependencies in financial data. The results indicate substantial risk reduction across multiple categories, including credit, liquidity, market, and operational risks, showcasing the model's robustness in handling financial uncertainties. The training and testing loss values stabilized at 0.0013 and 0.003, respectively, reflecting high prediction accuracy. Additionally, risk mitigation was evident, with credit risk dropping from 0.75 to 0.20, liquidity risk from 0.70 to 0.25, market risk from 0.65 to 0.30, and operational risk from 0.80 to 0.35. These findings validate the efficiency of deep learning in stress testing compared to conventional statistical models, which often struggle with nonlinear dependencies and real-time adaptability. Beyond technical advancements, the proposed framework offers significant implications for financial institutions, regulators, and policymakers. By providing a more accurate, data-driven approach to financial stress testing, it enables proactive risk mitigation, enhances regulatory compliance, and supports strategic decision-making. The ability to analyze vast amounts of financial data ensures timely identification of financial vulnerabilities, ultimately improving market stability. Future work could explore real-time stress testing applications, hybrid AI techniques combining ensemble learning, and macroeconomic forecasting integration. The proposed model establishes a foundation for AI-driven risk management, marking a significant step toward more resilient financial systems.

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